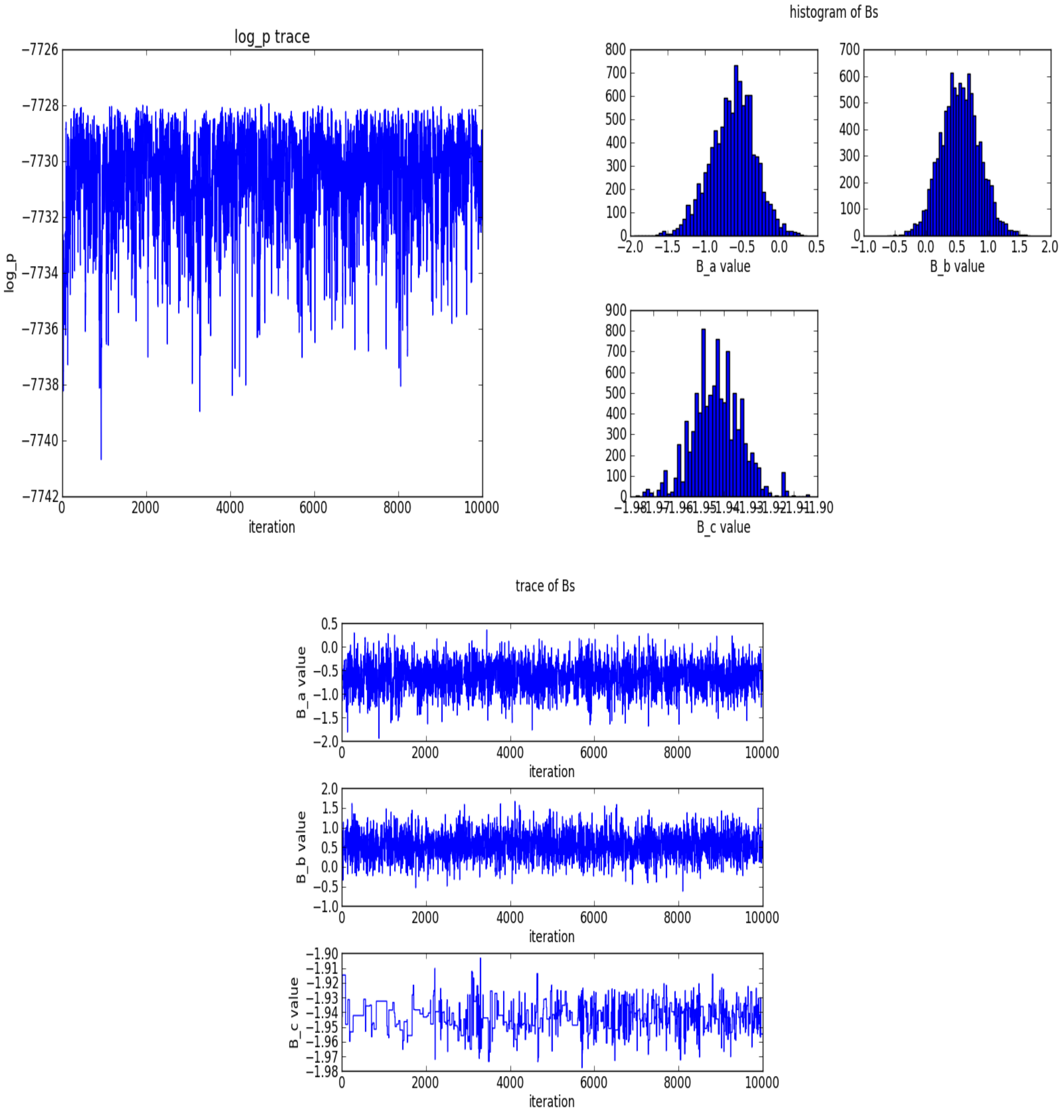

Figure 1: Plots for when simulating a, b, c

1 Simulation Results

To show that we can perform posterior inference to extract the posterior distribution of the model parameters B_a, B_b, B_c, we simulated data, fixing B_a, B_b, B_c. We simulated 2 different sets of variables. In both cases, we set $B_a = -1, B_b = 1, B_c = 2$. Also, we assume the presence of only 1 covariate, and generated 15 covariates equally spaced in the interval (-2,2) to use as the data X.

1.1 Simulating latent variables a, b, c

In the first scenario, we set $\phi^a = \phi^b = 0.5$ and $\phi^c = 0.2$, and for each X_i, generated a_i, b_i, c_i from the distribution specified by the model. For example, we generated a_i from a $Beta(B_a * X_i, \phi^a)$ distribution. This model does not contain any actual function values, since a, b, c are directly simulated/observed. To perform inference, we used the same model, fixing ϕ^a, ϕ^b, ϕ^c to the values used to generate a_i, b_i, c_i, and inferred the distribution of $P(B_a | a_i, b_i, c_i, \phi^a, \phi^b, \phi^c, X_i)$, and likewise for B_b and B_c.

1.2 Simulating data points $g^*(t)$

In the second scenario, we fix the ϕ^a, ϕ^b, ϕ^c and B_a, B_b, B_c as before. However, we do not simulate a, b, c directly. Rather, we picked a set of times $t_1 \dots t_m$, and for each of the 15 patients, simulated $g_i^*(t_j)$

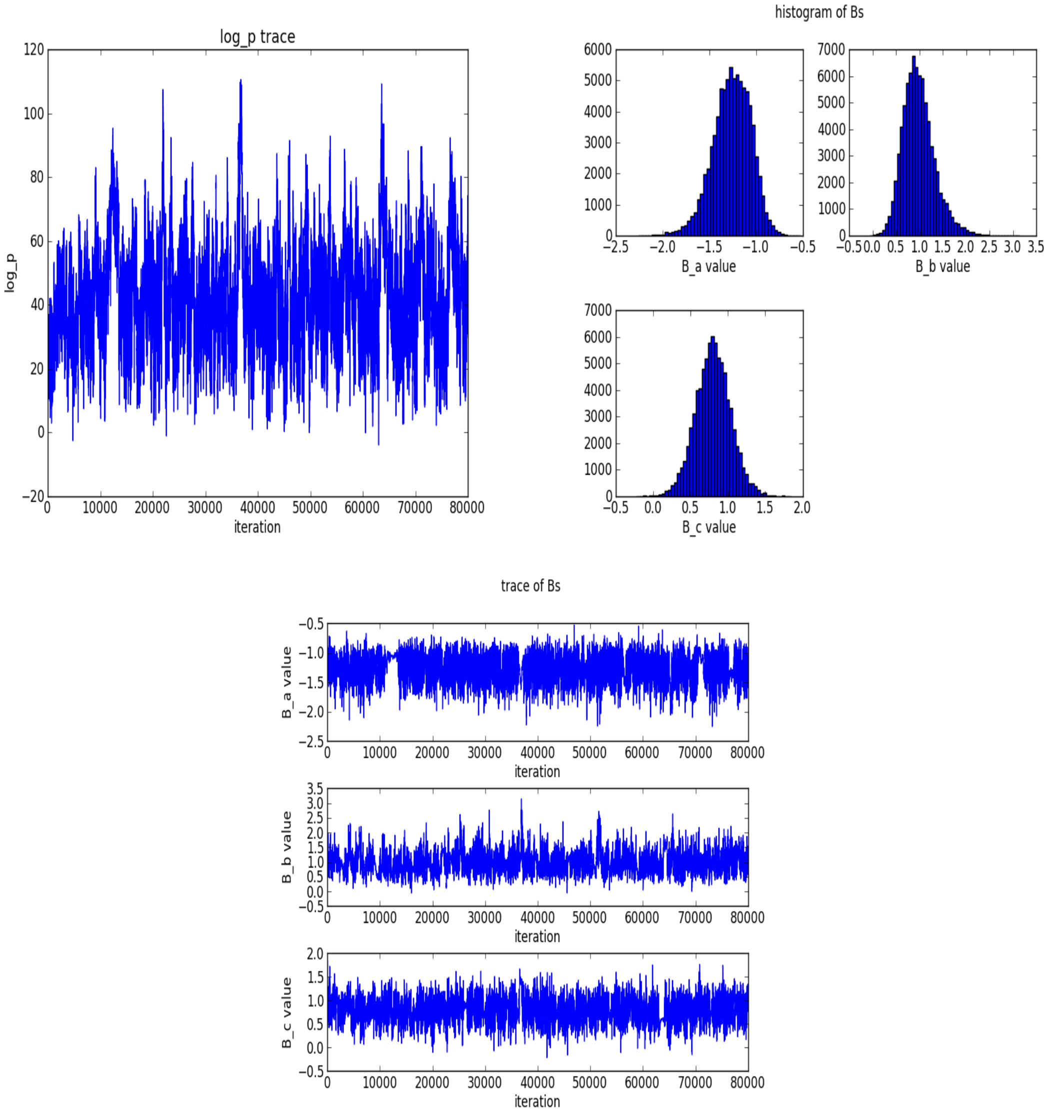

Figure 2: Plots for when simulating a, b, c

according to the model. We set $\phi^{noise} = 0.1$. That is, we first simulate a_i, b_i, c_i and once those are determined, simulate $g_i^*(t_j)$ for each time point t_j. To perform inference of B_a, B_b, B_c, we once again assume we know all noise parameters $\phi^a, \phi^b, \phi^c, \phi^{noise}$, and perform sampling to get the distribution of $P(B_a|\{g_i^*(t_j)\}, \phi^a, \phi^b, \phi^c, \phi^{noise}, X_i)$.